

A Detailed Survey of Cervical Cancer Using Classification and Segmentation Techniques

¹T.Vigneswari, ²R. Sivambiga, ³R. Shyamala Devi

¹Professor, ²PG Student, ³PG Student, Department of Information Technology

Sri Manakula Vinayagar Engineering College, Puducherry, India

¹vigneswarirt@gmail.com

²srsraju1997@gmail.com

³shyamaladevirajen@gmail.com

Abstract— Cervical cancer is the most dangerous disease, cervical cancer cannot be identified in the primary stage and it does not show any symptoms also. A numerous techniques are found for prediction and detection done through the classification and segmentation of cervical cancer. Different methodologies have been initiated for this cancer detection and prediction methods to find the accuracy and efficiency of cancer. The applications supported methodologies like Support Vector Machine (SVM), Convolutional neural networks (CNN), K-Nearest Neighbour (KNN), Screening technologies, Random Forest Classifier techniques are used for cancer detection and prediction which is elaborated in this work.

Keywords— Cervical cancer, Classification, Segmentation, Cancer detection and Prediction, Accuracy, Efficiency.

I. INTRODUCTION

The cervical cancer is the most dangerous cancer, for which women are prone to. They survive in a less rising place with a new cases expected nearly 578000 in 2018-2019 which is 85% of the new cases worldwide. The cervical cancer can be cured if it is diagnosed at an early stage. The cervical cancer is triggered due to sexually attained dirt. The cancer cell lesions in womanhood occurs after 30 years of age and further with a cost active way to protector the cervical cancer over method of screening and treatment.

The cervical cancer is controlled through major prevention, minor prevention, tertiary prevention and palliative care. The procedures for prevention includes vaccination in contradiction of HPV, screening method along with treatment of cancer lesions are analysis then the treatment for invasive cervical cancer are formed. The exposure of cervical cancer can be fixed with numerous tools and it can play a life-threaded role. The preventable process is done using different techniques. The methods which are used to identify the cervical cancer disease are HPV test, Pap test, Digital cervicography and colposcopy [1]-[6].

Machine Learning (ML) involves to get a given dataset for preparation of computer, and to predict the assets for a given new data set through training. ML attention on the development of databases which can be deviated over the exposed data and route for training and prediction elaborate with specific algorithms. Several ML methods have been developed and applied with different prediction and detection techniques for this cervical cancer. The clinical care and remote health monitoring [7]. The screening test can be helpful in preventing the cancer by identifying a lesion in which pre-cancer changes and abnormal growth of cells on the cervix surface are identified.

II. DETECTION PROCESS

The process of detection has some pre-processing stages and they are described below:

A. Pre-Processing:

The pre-processing stage is applied to improve the process which is based on the image and it increases the efficiency of the results obtained. In this paper, we have attached our dataset which is trained and established with various testing images which are listed below:

Pap Smear Cell Images:

Pap smear is used to identify the cervical cancer at the initial period and it is easy to recover by reviewing the cell naturally. A series of processing and examining steps have been taken place to categorize the specimen as normal or suspicious.

The important and demanding task in segmentation process is imaging system analytics, and the most challenging task is to analyse the minute part of the cervical cancer cells through Pap smear [8]. The quality less images will produce the poor analysis result in cell segmentation process. The Pap smear cell images are segmented and classified through the technique of deep learning, which is a combination of Machine Learning and Artificial Intelligence.

Endoscopic Images:

The endoscopic images are used to develop the mucosal visualization and enrich fine structure and micro-vascular images [9]. The professional endoscopic diagnosis can be enhanced with advanced imaging and it involves preparation and the use of authorized classification methods [10]. The endoscopic images are responsible for the point of care diagnosis [11].

HPV DNA Testing:

The possibility of finding the high hazard HPV disease is done through the HPV DNA test. This test is done to categorize the disease with high risk or low risk and it can be recognised [12]. Cervical cancer related to HPV has the following types: HPV-16(High risk), HPV-18(High risk), HPV-31, HPV-33, HPV-35, HPV-45, HPV-52, and HPV-58. Others risk types are not much common among crowd.

Colour Based Methods & Shaped Based Method:

The segmentation of cervix tissues is perplexing with the colour and shape in which texture and format of tissues are differ in a huge range. The cervix is present in the uterus region and it consists of different types of tissue specifically Squamous Epithelium- which is a flat tissue and pink in colour, Columnar Epithelium- which is unequal and red in colour, Acetowhite- a transient tissue. This texture analysis is used to identify the irregularity of the nucleus and the shape and form of the images are also assessed.

The size and colour strength helps to detect the falsely spotted nuclei at brighter images. Pixel colour intensity produce a super pixels range images which is easily recognizable. Cytoplasm nucleus' size, shape and texture are used to detect the precancerous stage in the cell and spot it immediately. Nucleus size shape texture is an easy recovery technique for high quality of images [13]- [15].

Clump Level Information:

The cells are displayed for pre-malignant growth testing. Malignant growth of cell tissue is created in the surface of more profound tissues and has the most possibility to be found in the uterus and close to the lymph hubs. At that point of malignant growth of cell will be invigorated away from the cervix in addition to that uterus has the range of dividers of the pelvis and the lower portion of vagina. It may be influenced around the lymph hubs at that point hinder the ureters, which results in cylinders truck pee from the bladder. The influenced bladder or rectums are emerging from the pelvis. It could also be spread to other organs like liver, bones, lungs and lymph nodes.

Microscopic Images:

The microscopic cervical images help to spot the real outcome of cancer which can be characterized and could be helpful in suggestion the patients about the suitable recovery measures [16]. The microscopic biopsy pictures uses the KNN technique to categorize the normal cell and cancer cell for the segmentation process.

Image Colour & Texture:

The colour based section represents the sign of suspicious CIN, and texture based section which makes available of important material to take intense care of the cervical tissues. To develop the classification performance through both colour and texture were it used over the individual [17-19].

Median Filter:

The image enhancements are used to diminish the clamour and it could be done with median filter. The median filters will professionally de-noise the image of cancer. It can also be a representative to remove the clamour of CT scan pictures of cervical cancer [20]. It is a nonlinear filter which governs the average value of one pixel, as of an ordered set.

Convolution:

Convolution is a linear development process that implements a filter matrix or kernel of an image and which outcomes with a new images.

III. FEATURE EXTRACTION:

The feature extraction is done with the process of segmentation, classification, data augmentation, and performance measures of phases. Here comes the detailed process.

Segmentation:

The division procedure is done through the Pap smear strategy. The precise cell division will be basic to isolate between the ordinary and irregular cells. After the division, explicit classifier is utilized to arrange the cells. If any segmentation errors is occurred in the intermediate process then it affects the whole segmentation process. The division is utilized to build up the precision rate (Accuracy) with various techniques.

The images obtained from the pre-process are analysed implementing a set of algorithms to detect the edges of the nucleus, and delineate them explicitly, separating these from the repose of the elements. The three essential objectives of article location are given as information pictures for division are each item in the picture are a rundown of jumping boxes, each bouncing boxes are related with a class mark, and each bouncing boxes and class name are related for the certainty score.

Classification:

Classification is method to which is used to categorise the data and allot a label to programmes. The type of supervised learning way of classier is Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF). The basic model of SVM is used to find out the feature space for make the most of the interval between positive and negative samples of preparation of data sets. It has classification and prediction abilities for unknown dataset samples.

Artificial Neural systems are the connectionist frameworks of action frameworks which is encouraged by the organic neural system it involves. The neural network is not an algorithm but it is an assembly for altered machine learning algorithm to work composed and progression the complex input data.

Random Forest Algorithm is developed to prepare a few choice trees and resolve on representations at that point utilize a different choice trees to assemble. It improves the prediction accuracy without the computational complexity. Random forests are regarded as most effective classification algorithm.

Data Augmentation:

The data augmentation is introduced for records and image quality. The dataset size increase with the model and the classification accuracy are over fitting while preventing through data augmentation. In this study, the data augmentation use both the classification and segmentation phase. Several datasets used for data augmentation. The training dataset images are selected randomly with the transformation for applications and it will be useful to the images. The classification process was used for rotation, zooming, shifting, de-noising, and colour transformations. The segmentation process is used for direction of flip (i.e. left, right, up, down), brightness, colour contrast, and cropping.

Performance Measures of Phases:

The performance measures are done with two phases: Segmentation and Classification to find the results of cancer cell. The performance measurements are done with the two processes that is segmentation and classification performance for the accuracy [21]. The presentation of division is done through exactness, review, a Zijdenbos Similarity Index (ZSI) and Specificity. The performance of classification is process through F1 score, sensitivity, and specificity. The performances are bringing about through the confusion matrix: True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN).

$$\text{Sensitivity (Recall)} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{F1 - score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2TP}{2TP + FP + FN}$$

IV. METHODS FOR DATA ANALYSIS:

Support Vector Machine:

Support vector machines (SVMs) is associated with a lot of regulated learning strategies, which is documented for performance of consortium and decline exploration utilizing information inquiry and example acknowledgment. Strategies fluctuate on the structure and properties of the classifier. The most regularly known SVM is the direct classifier, foreseeing each information part of class between two potential groupings. A progressively precise definition would prompt that a benefit vector machine constructs a hyper plane or a set of hyper planes to group all contributions to a high-dimensional or even endless space. The nearest qualities to the characterization edge is known as help vectors. The SVM will probably amplify the edge between the hyper plane and the help vectors.

Support vector machines are well-known and many think about them as the best off-the-rack classifier [22]. Besides, there are a wide determination of conditions and tool compartments that execute SVMs. Hence we applied SVMs to the issue of arranging infeasible experiments.

The classification score of cervical cancer are done through the method of parallel and serial combination for scatter plots. The SVM classifier specifies the chance of images fitting to both destructive and constructive class. The demonstration proportion of the help vector machine is finished with affectability for genuine positive rate and explicitness is utilized to quantify the genuine negative rate. The accuracy is done by overall proportion.

Convolutional Neural Network:

Convolutional Neural Network is an algorithm which contains an input images and assign importance for objects in the images and it will be differentiated form one to another. Input imaging used to separate the RGB colour plane in which ConvNet process is to reduce the image with easier form without losing any features of images and getting a strong prediction. Kernel is used as a convolution task for the source of high level features of input images. The valid padding is process for the convolved feature and decreases the dimensionality which is associated with the input and the same padding will be occurred with the dimensions of kernel.

The pooling layer is answerable for reducing the size of features and reduce the computational power needed to progress the data with dimension [23]. The Max Pooling and Average Pooling are the kinds of pooling layer and they are castoff for image covered done by the kernel and average of all the standards are return in an average pooling from the image covered through kernel.

The Fully connected neural network layer was the easier progression of learning certain combination of high level features which are considered through the output of Fully-CNN layer.

The cervical cancer images are the source of input in which the images are compared with one another and separated the image using the RGB colour plane it reduces the process with high prediction. The different channel are compared with the image pixel which are reduced for different channels that is valid padding, max pooling and it is process the fully connected neural network for flattened the channel and produce the output with high level feature images.

K-Nearest Neighbour (KNN):

The K-Nearest Neighbour Algorithm is second-hand to discrete the cell cores which is genuine concluded and done with separation manner starting the cytoplasm and it will classified. The accuracy for classification willpower not been long-established so the 5-

fold cross validation has been used to order the accurateness [24]. The system KNN is also used to categorise the regular and irregular cells through the microscopic biopsy images after the method of segmentation through k-mean technique.

Image Segmentation:

The image segmentation is done through two regions: the cervix region and specular reflection region. The cervix region is used to eradicate the unrelated data which is vaginal tissues and colposcopy. The cervical regions were matched with unconnected region [25]. They were accomplished with pre- and post-acetic acid trial imageries for segmentation.

$$F(x, y) = D_1 + D_2 + D_3 - D_4$$

Specular reflection is often stumble upon the colposcopy images and interferes with the exact changes of grayscale concentrations through the threshold method. The regions of interest are route through specular reflection.

A comparative study are done through the different performances which is used to detect the similarity of the classification and segmentation method then regulate the accuracy of these various techniques which are handle with cervical cancer process. The graph represents the accuracy percentage using the techniques and produces the efficiency for the various methods.

V. COMPARISON STUDY

Publisher	Dataset	Techniques	Accuracy
Wasswa WILLIAM, Andrew WARE, Annabella Habinka BASAZA-EJIRI, Johes OBUNGOLOCH [26].	Data of pap smear images dataset result	Fuzzy-C-means algorithm	99.35%
Jie Zhao, Quanzheng Li, Xiang Li, Hongfeng Li, Li Zhang [27].	917 pap test images of Herlev dataset	State-of-the art with Zij denbos Similarity Index	93%
C. LI, H.CHEN, L. ZHANG, N. XU, D. XUE, Z. HU, H. MA, H. SUN [28].	A gastric hematoxylinosin (HE) strained Histopathological image dataset	Multilayer hidden conditional random fields (MHCRFs)	93%
Haoming Lin, Yuyang Hu, Siping Chen, Jianhua Yao, Ling Zhang [29].	Five-fold cross-validation at Patient-level splitting through two- class, four class & seven class of classification task.	Convolution Neural Network	94.5%
Hongwei Du, Jun Liu, Han Lu [30].	The post & pre- acetic acid test images are extracted with Region of Interest (ROI) and diagnostic results are produced.	Back Propagation Neural Network	80.5%
Mahdin Rohmatillah, Sholeh Hadi Pramono, Rahmadwati, Hadi Suyono, Samuel Aji Sena [31]	Pap Smear dataset images are acquired from healthy & Cancerous Smears coming from the Herlev University Hospital (Denmark).	Support Vector Machine, Robust Kernel based Classifier and soft max classifier.	99.3%
Durrabida Zahras, Zuherman Rustam [32]	The dataset are collected from four different methods: Hinselmann, Schiller, cytology and Biopsy.	Deep Convolution Neural Network	90%
Robert P, Celine Kavida A [33].	The macroscopic cervical cancer images are collected with normal and abnormal cells for data set.	Support Vector Machine(SVM), K- Nearest Neighbour (KNN), Artificial Neural Network	94%

Table and Graph

The fig.1 represent the accuracy percentage. The Fuzzy-C-Mean is used for Pap smear image result identification and its accuracy percentage is very efficient. The dataset of Pap test images have processed through the state of the art which is compared to the Zij denbos similarity index. Histopathological image dataset are analysed through Multilayer Hidden Conditional Random Fields (MHCRFs). Convolution neural network, Deep Convolution neural network, Back Propagation neural network are the algorithm which can be resulted for the dataset which are collected from four different methods: Hinselmann, Schiller, cytology and Biopsy. Pap smear dataset images are acquired from healthy & Cancerous Smears which analysed through these methods Support Vector Machine, Robust Kernel based Classifier and soft max classifier. The two labels “(a)” and “(b)” are the parts of artwork which is Table and Graph.

Techniques	Percentage
Fuzzy-C-Mean	99.35
Similarity Index	93
MHCRFs	93
CNN	94.5
Back Propagation Neural Network	80.5
SVM	99.3
Deep CNN	90
SVM, KNN, ANN	94

Table 1 Comparative analysis for accuracy of cervical cancer using different techniques

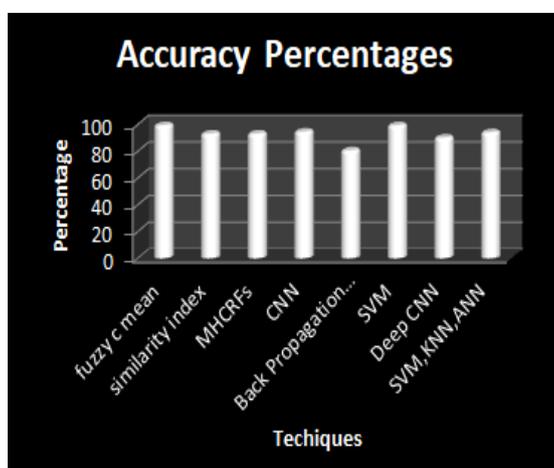


Fig.1 Accuracy percentage

“(a)”

“(b)”

VI. CONCLUSION

Even though many techniques and methods are used to differentiate the cells of the cervical part. Cervical cancer is difficult to identify because the symptoms are not available until it reaches to the final stages. This paper provides an overview of various methods that are available for predicting the cervical cancer. This paper elaborates the process of prediction and detection through the segmentation and classification. The dataset are determined through the testing of Pap smear images, microscopic images, pre- and post- acetic acid testing images, histo-pathological images, cytology images, and macroscopic images. We have also provided a detailed analysis about the various parameters that affect the accuracy of the prediction and also the selection of dataset to improve the prediction. The Pap smear images play a major role to identify the cervical cancer with the high accuracy of 99.3 % when used with techniques of machine learning algorithms. Further enhancement in improving the accuracy involves screening methods using the big data processing.

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